Collective Classification in Semantic Mapping with a Probabilistic Description Logic

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Abstract. Sensor data classification is very dependent on which features represent primitives. We consider line segments extracted from laser points as primitives, and focus on their collective classification into door or wall objects, so as to build semantic maps. Because features may have non-trivial characteristics, and sensor primitives may be inter-related in complex ways, we represent features of spatial relationships using a probabilistic description logic.

1 Introduction

Recent successes have raised expectations concerning the behavior of mobile robots in dynamic environments [21]. State-of-the-art applications construct precise spatial maps of static environments; however, autonomous robots need more than accurate spatial information when dealing with people or objects that display dynamic change. “Semantic mapping” focuses on the representation of an hierarchy of general objects in the environment, with their individual properties and inter-relationships. Broadly speaking, semantic maps must compactly encode rich information in a scalable manner.

Although there is no unique or precise definition for semantic maping in robotics, in the last five years many researchers have turned to spatial representations tagged with information like: "This segment of laser data is a door" or "This area of the occupancy grid is a room". As such, a semantic map typically means a labeled spatial map, and not really a map interwoved with deep semantic information. Few proposals really include semantic information in their robotic architecture by means of an ontology that relates objects in the environment. Clearly a more detailed look at semantic mapping is worth the study, because through semantic information we may expect to create more natural ways for robots to interact with humans and its environments.

Semantic mapping could deal with different sensor data inputs and output several different representations. Cameras could be employed to construct a map representation based in clusters of images representing different rooms [24]. Other proposals use 3D laser sensors to produce point cloud representations, that allows for object recognition [22], environment segmentation in floor and walls [1], and even the construction of a real map [15]. One interesting application relies in laser sensors that obtains horizontal slices at a fixed height of the environment to create bidimensional spatial maps. Semantic mapping in this context envolves the classification of line segments from already constructed 2D maps of indoor environments. This scenario was firstly proposed by Limketkai *et al.* [12] and latter was also approached by Wang and Domingos [19]. It is a scenario where one can explore different kinds of dependencies between the data, including spatial relationships and appearance. Both previous cited work employed models that combines first-order or relational logic with probabilities to produce line segments classification. The use of probabilities is justified because there is considerable uncertainty in associating dependencies with the possible classes of line segments, both due to the uncertain process of creating line segments from laser points and to changes in sensed objects [20]. And first-order logic is an expressive language that allows for a rich representation of complex relationships between different object in a compact way.

In this paper we focus exactly on the problem of laser data classification, using a combination of logic and probability to represent information extracted from sensor data. At the moment, we provide only probabilistic reasoning in our model while logic elements are used to describe the scenario and to obtain an ontology that could be explored in future applications. We chose to model this problem in a probabilistic description logic called CR$\mathcal{ALC}$, as it seems to provide a reasonable balance between flexibility and computational cost, to be explored in further developments. The next section briefly describes the probabilistic description logic CR$\mathcal{ALC}$. In Section 3, semantic mapping is discussed. Experiments are detailed in Section 4, followed by our conclusions.

2 Credal $\mathcal{ALC}$

A probabilistic description logic, called Credal $\mathcal{ALC}$ (CR$\mathcal{ALC}$), has been proposed recently [4,5,16], in a wave of related efforts [14]. In fact, the literature brings a variety of probabilistic description logics [7,9,10,11,13,3,18]; CR$\mathcal{ALC}$ is based on the popular $\mathcal{ALC}$ logic, adopts an interpretation-based semantics and resorts to the theory of Bayesian networks to allow for judgements of stochastic independence and to obtain inference algorithms.

The vocabulary of CR$\mathcal{ALC}$ contains *individuals*, *concepts*, and *roles*. Concepts and roles are combined to form new concepts using a set of *constructors* from $\mathcal{ALC}$ [17]: *conjunction* ($C \sqcap D$), *disjunction* ($C \sqcup D$), *negation* ($\neg C$), *existential* restriction ($\exists r.C$) and *value* restriction ($\forall r.C$). A *concept inclusion* is denoted by $C \sqsubseteq D$ and a *concept definition* is denoted by $C \equiv D$, where C and D are concepts; we assume in both cases that C is a concept name. We then say that C *directly uses* D; the relation *uses* is the transitive closure of *directly uses*. Also, the concept $\top$ denotes $C \sqcup (\neg C)$ for some concept C. As in $\mathcal{ALC}$, the semantics is given by a domain $\mathcal{D}$, a set of elements, and an interpretation mapping $\mathcal{I}$ that assigns an element to an individual, a set of elements to a concept, and a binary relation to a role. An interpretation mapping must also comply with constructs of the language; for instance, the interpretation of concept $C \sqcap D$ is $\mathcal{I}(C) \cap \mathcal{I}(D)$, while the interpretation of concept $\forall r.C$ is $\{x \in \mathcal{D} \mid \forall y : (x, y) \in \mathcal{I}(r) \rightarrow y \in \mathcal{I}(C)\}$. Additionally, CR$\mathcal{ALC}$ accepts *probabilistic inclusions* as follows. A probability inclusion reads

$$P(C|D) \in [\alpha_1, \alpha_2],$$

where D is a concept and C is a concept name. The semantics of such a probabilistic inclusion is, informally:

$$\forall x : P(C(x)|D(x)) \in [\alpha_1, \alpha_2], \tag{1}$$

where it is understood that probabilities are over the set of all interpretation mappings $\mathcal{I}$ for a domain $\mathcal{D}$. If D is the concept $\top$ then we write $P(C) \in [\alpha_1, \alpha_2]$. Probabilistic inclusions are required to only have concept names in their conditioned concept (that is, inclusions such as $P(\forall r.C|D)$ are not allowed). Yet another type of probabilistic assessement is possible in CR$\mathcal{ALC}$: for a role r, we can have $P(r) \in [\beta_1, \beta_2]$ to be made for roles, with semantics:

$$\forall x, y : P(r(x, y)) \in [\beta_1, \beta_2], \tag{2}$$

where again the probabilities are over the set of all interpretation mappings for a given domain.

Every ontology is assumed *acyclic*; that is, a concept does not use itself. If we write down an ontology as a directed graph where each node is a concept or role, and arcs go from concepts that are directly used to concepts that directly use them, we obtain that this graph must be acyclic. We refer to such a graph as an *ontology graph*. For instance, consider concepts A, B, C and the role r. C is a concept inclusion defined by $C \equiv A \sqcap \exists r.B$. In Figure 1.a we have the ontology graph for this example. Note that exists a node for general role $r\,(x, y)$ and another for the instantiation with concept $B\,(x)$, $\exists r.B\,(x)$. Concept inclusion $C\,(x)$ is composed by $A\,(x)$ and $\exists r.B\,(x)$.

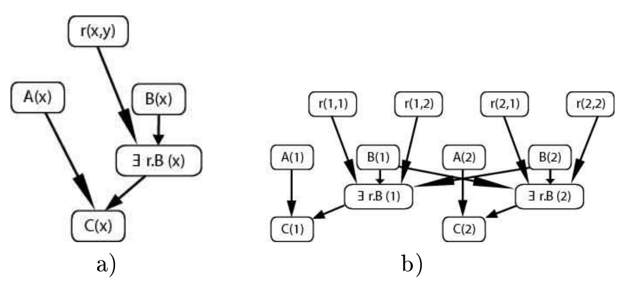

Fig. 1. Ontology graph

In short, the sentences written in the underlying description logic (with added probabilistic features) induce directed dependencies between instantiations of concepts. Under some additional restrictions (unique-names assumption, known and finite domain), any ontology expressed in CR$\mathcal{ALC}$ can be grounded into a Bayesian network, possibly with attached probability intervals [4,5,16]. That is, grounding an ontology with a finite and known domain leads to a *credal network* [6]. In Figure 1.b we have the grounded network for the ontology described in the previous paragraph, for a domain with only 2 individuals. Note that the entire ontology graph is repeated for each individual of the domain, with each concept instantiated for each individual and each role is instantiated with each pair of individuals. The probabilities of each sentence composes the CPT (*Conditional Probability Table*) of a particular node in the Bayesian network.

3 Semantic mapping with CR$\mathcal{ALC}$

We have used CR$\mathcal{ALC}$ previously to model some aspects of robotic semantic mapping. In [2] we proposed to segment robotic sensor data (odometry, gyro and distance measures) obtained from navigation through an indoor environment, based on the objects found in each different area. Rooms and Corridors are examples of possible areas to be found in an indoor environment. Such segmentation of the sensor data provides a scalable way to map larger environments, as each area could be mapped independently: as a result, several smaller areas are mapped and then merged together to construct the map.

The main limitation of that approach was that CR$\mathcal{ALC}$ models areas of the environment with relation to full objects detected by a image processing algorithm - inference does not start from sensor data itself. In our previous work, sensor data consisted of images that were processed by SIFT algorithm to detect objects whose signatures were trained previously.

But real robotic tasks must deal directly with uncertain sensor data. To do so, we wish to explore the flexibility and relatively low cost of CR$\mathcal{ALC}$; however, we do face some challenges to do so. In CR$\mathcal{ALC}$ we face a difficulty because the language models concepts (set of individuals) and a hierarchy over them, and not relations between individuals. There is no direct way to include a probabilistic dependency between two arbitrary constants or individuals. Some description logic languages that accepts *nominals*, allow us to specify individuals, like 'Brazil' and 'France'. But in semantic mapping domain it is impossible to consider in advance all the constants in the environment (all points, lines or planes that may exist).

The solution to this problem came from ideas presented in [19]. The trick is to include in the model, individuals or constants that are created from the combination of two segments; for example, there are two distinct segment lines, a and b. Then, if one is near the other, the constant ab is created (ba could also be created, but is identical to the first one). One way to specify in the model the conditional independences using the description logic language, is to create those kind of constants only when there is some dependency between the constants. Thus, it is not necessary to instatiate all possible combinations of segments. With that modification, it is necessary to differentiate concepts with

Table 1. Impact of features on the performance of classifier (extracted from [12]).

Environment	Lengths	Lengths+Neighbours	All
1	62.6%	88.5%	90.7%
2	58.7%	63.0%	93.5%
3	59.0%	79.2%	89.7%
4	51.8%	96.5%	97.7%
5	60.0%	68.5%	77.9%

primitive constant and concepts with composed constants. We now consider our application in more detail.

The scenario of interest is to take a bidimensional metric map, constructed using a SLAM algorithm, based on distances from a laser sensor, and to classificate each segment of the map in door or wall segments. Segments are extracted from laser data points following [8]. We do not propose to classify laser segments in real time as the robot constructs the map and localizes itself. Inferences are done offline, after the map has been obtained.

The trivial way to do that is to consider the length of each segment: doors tend to be of the same size, and walls have very variable lengths. But to make a robust classification, we need to consider further features of the segments. For instance, we should include dependences related to spatial relationships: points or line segments produced by laser sensor that are near one from another likely has the same classification.

To illustrate the importance of some features in the classification results, Table 1 lists the percentage of correct classification in five different environments, using only *Length*, *Length+Neighbours*, and all features together. As representative features are added (for instance spatial relationships), results are improved.

Some of the spatial features used by [23] are considered in our model and listed in Table 2.

Figure 2 depicts a Bayesian network constructed around two segments near each other and aligned along a line. Dashed line separates variables belonging to each of the segments. White nodes represents hidden variables; gray and black nodes represent observable variables; black nodes are continuous observable variables that must be discretized and gray nodes are discrete. Each segment is represented by *SegType* variable. Each has the *Length*, *Depth*, *SingleAligned* and *SharpTurn* properties. The relationships *Neighbours*, *Consecutive* and *Aligned* appears between each possible pair of segments. Beyond these properties and relationships, each segment could be attached to a line composed of aligned segments of the same type. In the scenario, only Wall objects could align to form a corridor. Each segment or aggregate of segments are represented by a discrete variable that contains its type (in the case of figure is *LineType*). *StarLine*, *EndLine*, *PreviousAligned*, *NextAligned* and *PartOf* characterize the properties of a segment inside a line.

This model, once implemented in CR$\mathcal{ALC}$, generates a large Bayesian network including all line segments extracted from the laser sensor, and considering all

Table 2. Spatial features.

SegType :	the segment is of the type, *Door*, *Wall*, or *Other*
LineType :	the line is of the type, *Door*, *Wall* or *Other*
PartOf :	the segment is part of the line
StartLine :	the segment is the start of a line
EndLine :	the segment is the end of a line
PreviousAligned :	there are segments aligned to this segment (preceding it)
NextAligned :	there are segments aligned to this segment (following it)
Aligned :	the angle between two segments is below some threshold, and so is the perpendicular distance between them
Neighbors :	the distance between the nearest end points of two segments is below some threshold
Consecutive :	there is no other segment's initial point between the initial points of the two segments
SingleAligned :	the angle between the segment and the average line it belongs to is below some threshold
SharpTurn :	the distance between the segment and its neighbor is below some threshold, and it is almost perpendicular to the average line
Length :	the length of the segment
Depth :	the depth of the segment, i.e., the signed perpendicular distance of the segment's midpoint to the nearest line

possible relationships between each two segments whose proximity is below some threshold. Classification is done through probabilistic inference in the graph using a MAP-based algorithm to promote collective classification. Recall that in collective classification, the class of each segment is decided based on the class of its neighbours.

An inherent problem in spatial mapping is the size of indoor environments. As each wall could be formed by a dozen line segments, the number of constants to be considered, and consequently the number of spatial relations to put in the model, are prohibitive. In our experiments, we have decided to partition the dataset in smaller sets, so we could handle the problem with the tools available. Figure 3 shows a corridor extracted from a map. The corridor is formed by a set of segments that must be classificated in doors, walls and others.

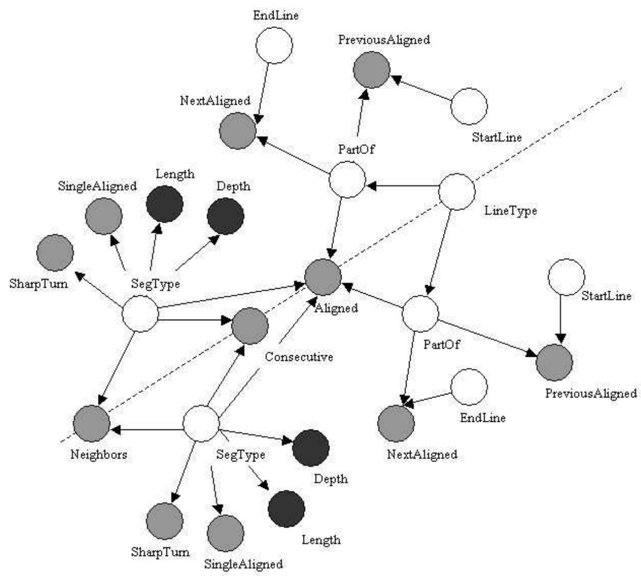

Fig. 2. A sample diagram.

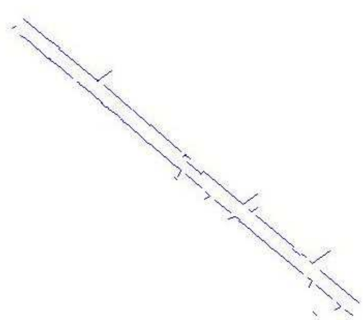

Fig. 3. Example of the scenario of classification of line segmentes.

4 Experiments

The experiments consist of teleoperation of a robot with a laser sensor through an indoor environment. As the robot navigates, laser readings and odometry are collected to be processed later, so as to produce a metric map. Any standard algorithm could be used to produce a consistent map. Basically, it is necessary to transform relative measures, obtained as the robot traverses the environment, into a global coordinate system, by dealing with uncertainty measures of the laser and the robot position. It is important to have line segments formed by laser points adequately positioned in the world, because CR$\mathcal{ALC}$ does not deal with uncertainty regarding spatial coordinates.

Although we collect some data with our own robot (Figure 4), and tested our model with it to determine the parameters, we have decided to report results for a dataset available online in the Radish repository, as other works that approached that same problem, using instead RMN and MLN models, used that dataset.

Fig. 4. Robot Pioneer 3-AT used in the experiments.

A restriction found in probabilistic models that incorporates logic elements is the type of random variables that are allowed. Often a continuous random variable for the length of the segment constructed from laser points must be discretized in a finite set of possible lengths. In our model, it was necessary to turn some numerical quantities into discrete values, as with variable *Length*. We considered six different values of lengths for doors and walls, based on our observed data.

The values for our conditional probability tables (the parameters of our model), were determined experimentally using our own experience in this kind of problem. These values are listed in Table 3.

Inferences were performed using the package *SamIam* (available at the address *http://reasoning.cs.ucla.edu/samiam/*). We selected MAP-based explanations generated by an approximate algorithm. Through MAP, we produced collective classification, and decided on each line segment label considering the labels of its neighbours.

Table 4 shows results obtained by MAP inference in a scenario with 70 line segments. In each column represents a range (i.e., 1-10 or 11-20) in the line segments considered. Rows indicate an exact line segment inside the range of the respective column. Observing the results, we have around of 75% accuracy, considering only *Length*, and *Neighboor* and *Aligned* features. It is hard to make a quantitative comparison between our results with Limketkai's RMN and Wang's MLN, because the features used in their experiments are not clearly given; nevertheless, qualitatively, results with CR$\mathcal{ALC}$ are similar to the ones obtained with their probabilistic logic models.

Table 3. CPTs used in the model.

	door	wall	other
length_1	0.0	0.2	0.25
length_2	0.1	0.15	0.15
length_3	0.8	0.15	0.2
length_4	0.1	0.15	0.15
length_5	0.0	0.15	0.25
length_6	0.0	0.2	0.0

door	0.3
wall	0.4
other	0.3

Roles

Neighbour									
s_1	door			wall			other		
s_2	door	wall	other	door	wall	other	door	wall	other
true	0.6	0.8	0.6	0.6	0.6	0.6	0.7	0.8	0.5
false	0.4	0.2	0.4	0.4	0.4	0.4	0.3	0.2	0.5

Aligned									
s_1	door			wall			other		
s_2	door	wall	other	door	wall	other	door	wall	other
true	0.5	0.3	0.3	0.3	0.5	0.3	0.3	0.3	0.5
false	0.5	0.7	0.7	0.7	0.5	0.7	0.7	0.7	0.5

Table 4. Inference results.

Calculated/Correct	1-10	11-20	21-30	31-40	41-50	51-60	61-70
1	**wall/wall**	**wall/wall**	wall/door	**other/other**	door/wall	**door/door**	**door/door**
2	other/wall	door/wall	**wall/wall**	wall/door	**door/door**	**wall/wall**	wall/other
3	**door/door**	wall/other	**wall/wall**	**wall/wall**	**wall/wall**	**wall/wall**	**door/door**
4	**wall/wall**	**wall/wall**	**wall/wall**	wall/other	**door/door**	wall/other	**wall/wall**
5	**wall/wall**	**wall/wall**	**wall/wall**	**door/door**	**wall/wall**	**wall/wall**	**wall/wall**
6	wall/other	**door/door**	**door/door**	door/wall	**door/door**	**door/door**	**wall/wall**
7	wall/other	**door/door**	door/wall	other/wall	**wall/wall**	**wall/wall**	**wall/wall**
8	**door/door**	other/wall	**door/door**	wall/other	**wall/wall**	**wall/wall**	**wall/wall**
9	**wall/wall**	**door/door**	**other/other**	**wall/wall**	**wall/wall**	**wall/wall**	**door/door**
10	**wall/wall**	wall/other	**wall/wall**	**door/door**	**door/door**	**wall/wall**	wall/other

5 Conclusion

This article proposes semantic mapping techniques based on the classification of line segments from a metric map into *Doors*, *Walls*, or *Others* elements, using CR$\mathcal{ALC}$ as a representation language. Metric maps are constructed by a standard SLAM algorithm, so as to obtain a precise spatial positioning of each line segment and then to determine features. To do so, we used constants formed by the combination of two simple constants. With these new constants, we included features of neighborhoods and properties of alignments.

We chose a probabilistic description logic due to its compact encoding of the needed knowledge; as a result less parameters must be specified. Collective classification proceeds as inference over an instantiated probabilistic graph using approximate reasoning; all labels are decided together in a single run.

Preliminary results obtained with CR$\mathcal{ALC}$ show that it can handle classification of robotic sensor data. The next step is to further extend this labeling to create an automatic topological map starting for the labels of the metric map, and also to use the same technique to create 3d maps. Besides that, we are trying to introduce DL reasoning in the model through extension of $\mathcal{ALC}$ to some description logic that accepts spatial reasoning.

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